

FINAL REPORT SUBMITTED TO AOARD

David Chan, Professor of Psychology, Singapore Management University

Research Project Title:

Modeling Change over Time:

Conceptualization, Measurement, Analysis, and Interpretation

The concept of *change over time* is fundamental to many phenomena examined in research in the behavioral and social sciences. In many areas of investigation (e.g., skill acquisition, organizational newcomer socialization), the focus of the study is explicitly on the conceptualization and assessment of change over time. In military contexts, explicating the various facets of change over time is critical when tracking how variables such as soldier adaptation, stress, strain, and understanding and commitment to mission changes in both short-term and long-term operations either of a combat or non-combat (e.g., humanitarian assistance) nature. For example, soldier commitment to mission may undergo a change process represented by a conceptual differentiation over time such that the perception moves from a unitary or global conceptualization at initial phases to several distinct but correlated dimensions in intermediate phases to separate unrelated dimensions in final phases. Specifically, initial conceptualizations may be best represented by a global and unitary commitment dimension but later conceptualizations may be best represented by distinct and relatively unrelated dimensions such as affective (emotional), normative (obligatory), and continuance (instrumental) commitments.

Even when the concept of change over time is less explicit, most studies require some form of theory or conceptualization of change over time and some form of quantitative assessment or analysis of change is performed for the purpose of making substantive inferences. Because change over time is fundamental in almost all behavioral and social science phenomena, it is important that researchers possess a good working knowledge of the critical issues involved in the modeling of change over time.

The objective of this research report is to provide a state-of-the art review of the issues and methods relating to the modeling of change over time. The focus is on the quantitative assessment of the concept of change of time, which includes issues of conceptualization, measurement, data analysis, and interpretation. The rationale and motivation for this research originated from the author's observations (specifically in the past

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14. ABSTRACT The objective of this research report is to provide a state-of-the art review of the issues and methods relating to the modeling of change over time. The focus is on the quantitative assessment of the concept of change of time, which includes issues of conceptualization, measurement, data analysis, and interpretation. The rationale and motivation for this research originated from the author's observations (specifically in the past decade in the capacities of journal editor, reviewer, symposium discussant, and workshop leader) on the need for a comprehensive and relatively non-technical reference on and integration of various issues in the modeling of change over time that will facilitate researchers studying substantive change phenomena who may not be methodological experts on analysis of longitudinal data.					
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decade in the capacities of journal editor, reviewer, symposium discussant, and workshop leader) on the need for a comprehensive and relatively non-technical reference on and integration of various issues in the modeling of change over time that will facilitate researchers studying substantive change phenomena who may not be methodological experts on analysis of longitudinal data.

Although there are several books, book chapters, and journal articles on longitudinal data analysis, they tend to be highly technical and narrow in focus in presenting specific data analysis issues (e.g., debate on the use of difference scores, description of a specific technique of longitudinal analysis) and there is little or no attempt to relate specific analysis issues to the *multifaceted* concept of change over time in such a way that integrates conceptualizations, measurement, analysis, and interpretation of findings. By providing a comprehensive and integrative approach to modeling change over time, this research fills an important gap in the extant methodological literature and builds an interface between highly technical methodological works and researchers investigating substantive phenomena in the behavioral and social sciences. Other specific outstanding features of this research, which are not present in existing research literature on longitudinal data analysis, include (1) specifying the fundamental questions on change over time, (2) discussing the problems with application of traditional techniques to assess change over time, (3) explaining conceptual issues and technical details on the assessment of measurement invariance over time, (4) discussing and illustrating multivariate assessment of change, (5) discussing the problems of common method variance in the study of change over time, and (6) explicating the study of change over time in the contexts of cross-cultural research and multilevel research.

This final report summarizes the comprehensive and integrative approach to the issues and techniques of modeling change over time. Given the wide applicability of the methodological issues discussed and its relatively non-technical nature, this final report will have appeal to empirical researchers involved in substantive research including military studies, in addition to those primarily interested in measurement and methodology. The target audience will include researchers from many diverse fields of substantive research including those from disciplines in the organizational, behavioral, and social sciences. Specific disciplines that will be especially relevant include military psychology, industrial and organizational psychology, marketing, organizational behavior, human resources management, developmental psychology, clinical psychology, social psychology, sociology, political science, and education. It is hoped that this final report may be used as a regular concise but relatively comprehensive reference for empirical researchers.

Modeling Change over Time

For many decades in I/O psychology, predictor-criterion relationships have been described in terms of static models of the criterion without any attention paid to the temporal aspects of the criterion constructs including what and how changes may occur over time. Consider the example of job performance models. An individual's job performance may change over time in various ways (e.g., increase/decrease in level, changes in the number/nature of underlying dimensions) and these intraindividual changes are important for understanding and predicting job performance. For example, when performance changes over time either in terms of level or dimensionality, using a sample of job incumbents with varying levels of job tenure in a validation study could affect and confound estimates of validity and the interpretation of predictor-criterion relationships.

Advances in longitudinal analytical strategies, especially those that involve latent variable modeling, provide us with both the conceptual basis and statistical method to hypothesize, test, and interpret criterion (e.g., performance) changes over time which in turn allows us to draw practical implications (e.g., personnel selection issues) such as changes in test validities, changes in mean levels of the criterion, changes in rank order of individuals' criterion scores, and changes in criterion dimensionality (i.e., number and/or nature of dimensions).

The analysis of change over time has to be guided by the conceptualization of change over time. By first specifying the specific facet of change over time, appropriate longitudinal designs and data analytic techniques can be applied to implement research that answers important questions relating to criterion changes over time. In the example of job performance changes, these questions may include the nature of new performance dimensions associated with changes in job demands or different points in time over the individual's job tenure; describing, predicting, and explaining the form of the intraindividual change trajectory (e.g., linear versus quadratic, increasing versus decreasing) and individual differences in the rate of intraindividual change; and modeling associations among performance dimensions and the trajectories by which they change over time.

Fundamental Questions on Changes Over Time

The various specific facets of change over time are related to distinct fundamental questions that may be asked of the nature of change that may occur over time. Chan (1998) explicated nine such questions. These questions highlight the complexities involved when considering change over time and the importance of clarifying the specific question asked of

the change phenomenon and relating it to the analytical strategy and the substantive inferences made from data. These questions, addressed in detail in Chan (1998), are briefly summarized below.

Q1. Is an observed change over time (and observed between-group differences in change over time) due to meaningful systematic differences or random fluctuations resulting from measurement error? If measurement error is not adequately taken into account when specifying the data analysis model and estimating the parameters, results of the analyses can be severely affected by measurement error. The classic independence of errors assumption, which is common among many traditional data analysis procedures, may be violated when assessing change over time in longitudinal designs, particularly when the longitudinal data are collected on measurement occasions closely spaced together using identical measures.

Q2. Is the change over time reversible? The question on the reversibility of change over time can be construed in terms of the functional form of the intraindividual growth (change) trajectory. For example, monotonically increasing or decreasing (e.g. linear) functional forms represent irreversible (within the time period studied) change in the sense that there is no returning or restoring to previous levels on the focal variable, at least during the period under investigation. On the other hand, a non-monotonic functional form (e.g., an “inverted U”) would represent reversible change over time.

Q3. Is the change over time proceeding in one single pathway or through multiple different pathways? Two (or more) groups of individuals may follow the same or different trajectories as they proceed from one time point to another (through intervening time points measured in the study). For example, in a four-time point study (e.g., organizational newcomer adaptation study with adaptation outcomes measured at 4 time points equally spaced at one-month measurement interval), two groups (e.g., locals and expatriates) may have the same value on the focal variable at initial status (Time 1) and at end point (Time 4) but one group follows a positive linear trajectory and the other follows a positively accelerated monotonically increasing trajectory. That is, change from one value of the focal variable at Time 1 to another value at Time 4 could proceed through multiple different pathways.

Q4. Is the change on the quantitative variable proceeding in a gradual manner or is it best characterized as large magnitude shifts at each time interval? Quantitative change over time may proceed gradually as characterized by a linear trajectory with a low slope or it may be characterized in terms of large magnitude changes as represented by a high slope.

Q5. Is the change over time (or across groups) to be considered as alpha, beta, or gamma change? Golembiewski, Billingsley, and Yeager (1976) distinguished three types of change: alpha, beta, and gamma. Alpha change refers to changes in absolute levels given a constant conceptual domain and a constant measuring instrument. For example, if job satisfaction was adequately measured both at Time 1 and Time 2 in terms of reliability and validity such that the same construct was measured at both time points and with the same precision, then the difference in the satisfaction scores between the two time points represent an alpha change in satisfaction and the change may be directly interpreted as a change in the absolute level of job satisfaction. We can meaningfully speak of alpha change only when there is measurement invariance of responses across time. Measurement invariance across time exists when the numerical values across time waves are on the same measurement scale. Measurement invariance could be construed as absence of beta and gamma changes. Beta change refers to changes in absolute level complicated by changes in the measuring instrument given a constant conceptual domain. Beta change occurs when there is a recalibration of the measurement scale. That is, in beta change, the observed change results from an alteration in the respondent's subjective metric or evaluative scale rather than an actual change in the construct of interest. For example, because of the respondent's increased leniency in ratings over time, a rating of 6 given at Time 2 may be defined by the respondent as was rating of 5 at Time 1. Gamma change refers to changes in the conceptual domain. Gamma change (i.e., change in the meaning or conceptualization of the construct(s) of interest) can take a variety of forms. For example, in the language of factor analysis, the number of factors (a factor representing a construct) assessed by a given set of measures may change from one time point to another. To illustrate, in a study of changes in performance over time, performance may undergo a type of gamma change represented by factorial integration of performance measurement so that performance components (factors) become increasingly interrelated over time such that performance at early time points are best represented as multiple distinct and relatively uncorrelated factors, at mid time points are best represented as multiple highly correlated factors and at later time points are best represented as a single factor.

Q6. Is the change over time occurring at the individual, group, or both levels of conceptualization? Change over time can be conceptualized and assessed at the individual level, group level (e.g., team, department), or both levels. Any analytic technique that is restricted to only one level of conceptualization and analysis is limited in an important way because the assumption of no or "irrelevant" change at the other level is not tested.

Q7. In addition to detecting interindividual differences in intraindividual change, can we predict (and hence increase our understanding of) these differences? Individuals may systematically differ in the way they change over time. We can increase our understanding if the longitudinal modeling can incorporate additional variables and assess their efficacy in predicting the different aspects of these individual differences (e.g., individual differences in rate of change, individual differences in trajectory forms).

Q8. Are there cross-domain relationships in change over time? Changes in one focal variable may be systematically related to changes in another focal variable. For example, during the period of newcomer adaptation, the rate of change in information seeking may be positively correlated with the rate of change in task mastery. An adequate longitudinal modeling procedure would allow us to explicitly model these cross-domain relationships.

Q9. Do the various relationships with respect to specific facets of change over time vary or remain invariant across groups? Different groups may either share or differ in the various specific facets of intraindividual changes. An adequate longitudinal modeling procedure would allow us to explicitly model and test the various hypotheses concerning between-group differences or similarities in change over time.

Limitations of Traditional Techniques for Modeling Changes Over Time

Chan (1998) provided a detailed description of these nine questions and explained why traditional techniques such as difference scores analysis, repeated measures ANOVA, and time series are limited in their ability to adequately address these questions.

To illustrate the limitations of traditional techniques for modeling changes over time, consider time series models which are probably the most commonly used longitudinal data analysis technique. Time series models were developed to describe a relatively long series of observations typically consisting of at least twenty or thirty time points. In general, time series models may be classified into time domain and frequency domain models. Autoregressive integrated moving average (ARIMA) models are representative of time domain models (e.g., Box & Jenkins, 1976) whereas spectral analysis models are representative of frequency domain models (Larsen, 1990).

Time domain and frequency domain models differ in how they represent the same time series information. Time domain models analyze the longitudinal data and make inferences based on the autocorrelations in the sequence of observations. Autocorrelation refers to the correlation between later items in a time series and earlier items (when the time

series is completely random, the autocorrelation is zero). The time series is expressed in terms of autoregressive or some other time-based parameters. In these models, a given observation in time is characterized as a weighted function of past observations of the same underlying process. These time series models, such as ARIMA models, are typically used for forecasting purposes. Frequency domain models, on the other hand, express and account for the time series data in terms of trigonometric functions such as sine and cosine functions. These functions are used to represent rhythms or cycles assumed to underlie the time series data. Clearly, the choice between the two classes of models is dependent on the nature of the research question at hand. For example, questions that forecast time points call for time domain models whereas those that assess rhythms or cycles within the data call for frequency domain models.

Although both classes of time series models have potential applied value in substantive longitudinal research in I/O psychology (e.g., time domain models can be applied to the study of predicting future job performance rankings from past job performance rankings; frequency domain models can be applied to the study of mood variability at the workplace), the requirement of a large number of repeated measurements in the longitudinal design limits the actual applied value of these time series models, at least in the current state of I/O research. More importantly, as explained in Chan (1998), time series models are not well equipped to assess the various aspects of intraindividual change discussed above. For example, time series models cannot be readily used to model interindividual differences in intraindividual changes. It is possible to fit a time series to an individual's repeated observations (hence compare different individuals' function by comparing distinct time series models) or to the summary statistics of a group of individuals (hence compare different groups' functions by comparing distinct time series models), but it is not possible to do both at the same time. That is, it is not possible, within a single time series model, to examine a group's intraindividual change function at the aggregate (group) level and, at the same time, individual differences in intraindividual change functions.

One fundamental question on intraindividual change is whether the same construct is in fact being observed over time and, if so, whether it is being assessed with the same precision. This issue of measurement invariance (of repeated responses on the identical measure) over time is statistically fundamental because virtually all the traditional techniques such as time series models, repeated measures ANOVA and difference scores analysis are applied in a manner that assumes, rather than directly tests, the assumption of measurement invariance of intraindividual repeated responses over time. In addition, depending on the

research question, certain measurement invariance questions may be theoretically interesting in their own right (i.e., reflecting a substantive intraindividual change process), apart from the issue of reflecting a statistical hurdle to be cleared prior to assessing substantive intraindividual change. For example, a lack of measurement invariance of responses over time may reflect a substantive intraindividual change process associated with a type of gamma change in performance dimensions over time.

Latent Variable Approaches to Modeling Changes Over Time

Latent variable approaches are well suited for longitudinal modeling because they can explicitly take into account both cross-sectional and longitudinal measurement errors. Hence, the researcher is able to model a variety of error covariance structures and assess any distorting effects that cross-sectional or longitudinal measurement errors may have on the various parameter estimates of true change. In addition, latent variable approaches are highly flexible and powerful because a variety of latent variable (i.e., SEM) models can be fitted to the longitudinal data to describe, in alternative ways, the change over time.

Latent growth modeling (LGM) offers a direct and comprehensive assessment of the nature of true intraindividual changes and interindividual differences in these changes. LGM also allows these differences to be related to individual predictors. A LGM model can be elaborated into a multiple-indicator latent growth model (MLGM). MLGM is essentially a LGM analysis in which the focal variable of change is modeled as a latent variable represented by multiple indicators. Technical details of LGM and MLGM are described in Chan (1998).

LGM represents the longitudinal data by modeling interindividual differences in the attributes (i.e., parameters) of intraindividual changes over time (i.e., individual growth curves). In an LGM analysis, we can estimate the means and variances of the two growth parameters (intercept and slope factors) and examine if the two parameters are correlated with each other. The LGM analysis can also be used to examine associations between the growth parameters and individual difference predictor variables. For example, in newcomer adaptation research, we can use LGM to predict initial status and rate of change in information seeking from proactive personality (Chan & Schmitt, 2000). Different univariate latent growth models can also be combined to form a multivariate latent growth model. In a multivariate growth model, parameters from different change trajectories can be correlated to examine cross-domain associations (i.e., relationships between two focal variables being examined for intraindividual change over time). For example, in a study of interpersonal

relationships, rate of change in relationship building can be correlated with rate of change in social integration. One or more predictors can also be included in the multivariate model, thereby allowing hypotheses regarding differential predictions (using the same individual predictor) of intraindividual change across domains can be tested. Finally, LGMs (univariate or multivariate) can be fitted simultaneously to different groups of individuals (e.g., gender, ethnic, occupational, experimental groups) and multiple-group LGM analyses can be performed to test for across-groups invariance of one or more of the specified relationships in the latent growth model.

To incorporate measurement invariance concerns in the model specification, LGM can be extended to a MLGM in which the focal variable of change is modeled as a latent variable assessed by multiple indicators as opposed to a manifest variable typically the case in prior work on LGM. The use of multiple indicators in a latent growth model allows both random and nonrandom measurement errors to be taken into account when deriving the intercept and slope/shape factors. The use of multiple indicators to assess the focal construct allows reliable (nonrandom) variance to be partitioned into true score common (construct) variance and true score unique variance. True score unique variance is nonrandom and it is that portion of variance in a measure that is not shared with other measures of the same construct. In LGM, the same measures are repeatedly administered over time. Hence, a failure to partition nonrandom variance into true construct variance and unique variance leads to distorted (inflated) estimates of true change in the focal construct over time. Because only scale/composite level but no item-level (multiple indicator) information on the focal variable is used in the standard LGM, the procedure does not provide the isolation of nonrandom error variance from reliable variance and it takes only random errors into consideration. MLGM addresses the problem.

Chan (1998) demonstrated how the above questions on measurement invariance, functional forms of intraindividual changes, and other fundamental questions on change over time may be answered in an integrative two-phase latent variable analytical procedure that combines longitudinal means and covariance structures analysis and multiple-indicator latent growth modeling. In Phase 1 of the procedure, longitudinal mean and covariance analysis, which is similar to longitudinal factor analysis except that both the indicator intercepts and factor means are also estimated, is used to examine issues of measurement invariance across time and across groups. Establishing invariance provides evidence that results of subsequent growth modeling constituting Phase 2 of the procedure are meaningful. By building invariance assessments as the first logical step to longitudinal modeling, this integrative

procedure contrasts with the analytical models that left untested the assumption of measurement invariance across time or groups. In addition to invariance assessments, Phase 1 of the procedure helps in the preliminary assessment of the basic form of intraindividual change by identifying the constraints on the patterns of true score (factor) means and variances over time. In Phase 2, multiple-indicator longitudinal growth modeling is used to directly assess change over time by explicitly and simultaneously modeling the group and individual growth trajectories of the focal variable as well as their relationships to other time-invariant predictors and/or time-varying correlates (i.e., growth trajectories in a different domain). As explained in Chan (1998), longitudinal mean and covariance analysis and multiple-indicator latent growth modeling together provide a unified framework for directly addressing the various fundamental questions on change over time.

Chan (1998) provided a complete instructive numerical example, with LISREL command specifications, on how to fit multiple-indicator latent growth models and interpret the results.

Longitudinal covariance structures analyses such as longitudinal factor analysis, longitudinal means and covariance structures analysis, and latent growth modeling are appropriate when the latent variables are continuous in nature. When the latent variables are discrete (i.e., categorical) in nature, latent class analysis is appropriate. When latent class modeling is applied to discrete longitudinal data, the analysis is known as latent transition analysis which allows the researcher to specify and test stage-sequential development or changes over time. An excellent introduction to latent class analysis and latent transition analysis is provided by Collins and Wugalter (1992). Recently, Muthen (2004) developed an inclusive framework known as general growth mixture modeling which combines latent growth models and latent class models. This general framework allows the researcher to identify latent classes characterized by different patterns of latent growth. These mixture models are useful because they allow us, in a single integrated analysis, to identify groups of individuals with qualitatively different growth trajectories.

Not all latent variable approaches are suited for modeling changes over time. For example, autoregressive latent modeling, which is one of the simplest latent variable approaches, is not adequate for the analysis of longitudinal data representing intraindividual change over time. Autoregressive models estimate scores on a variable based on values of the same variable. Proponents of the inclusion of autoregressive models in the longitudinal modeling of intraindividual change argue that the autoregressive effect (the effect of the Time 1 measure on the Time 2 measure of the same variable) is a legitimate competing explanation

for an observed effect and therefore must be included before causal inferences can be made regarding the influence of other predictors of change over time. The inclusion of autoregressive effects in longitudinal modeling of intraindividual change is problematic because they tend to remove all potentially important predictors of change except those that predict changes in rank order of the observations over time. For example, in a monotonically stable growth process in which all individuals increase at a constant rate (i.e., linearly) while maintaining the same rank order, the important predictors of the individual slopes would be eliminated with the inclusion of autoregressive effects. The autoregressive model fails when intraindividual change is accompanied by high-rank-order stability over time (Stoolmiller & Bank, 1995). In addition, the autoregressive effect is questionable as a true causal effect and researchers have argued that proponents of the application of autoregressive latent models in longitudinal modeling have misinterpreted the autoregressive effect as a parameter representing true causal effect when it is in fact a stability coefficient representing the boundary or initial values of the system. For more comprehensive discussions of the problems associated with including autoregressive effects in longitudinal modeling of intraindividual change, see Rogosa and Willett (1985) and Stoolmiller and Bank (1995).

The Multilevel Structure of Longitudinal Data

The preceding section on modeling multilevel phenomena discusses the “traditional” type of multilevel data in which individuals are nested within groups. In modeling changes over time using longitudinal data, we are in fact dealing with a type of multilevel data in which the multilevel structure is less obvious. Longitudinal data are obtained from measurements repeated on the same individuals over time, and hence a multilevel structure is established with the repeated observations over time (Level 1) nested within individuals (Level 2). While the multilevel analysis of cross-sectional grouped data is concerned with interindividual differences associated with group membership, multilevel analysis of longitudinal data is concerned with modeling intraindividual change over time. Although multilevel regression models can also be used to analyze these changes over time (e.g., Bryk & Raudenbush, 1992), the issues of changes over time are often very complex and may involve facets of change over time (e.g., conceptual changes in the constructs, changes in calibration of measurement, various types of time-related error-covariance structures) that are not readily handled by multilevel regression models. In modeling change over time, we are primarily concerned with describing the nature of the trajectory of change and accounting for the interindividual differences in the functional forms or parameters of the trajectories by

relating them to explanatory variables. The explanatory variables may be in the form of experimentally manipulated or naturally occurring groups, time-invariant predictors, time-varying correlates, or the trajectories of a different variable. Latent growth modeling and its extensions are well suited to address these issues. Chan (1998) provided a detailed review of these issues and the application of latent growth modeling techniques, as well as an overview comparison between latent variable models and multilevel regression models.

Latent variable models can be specified and tested using any of the widely available structural equation modeling programs such as AMOS (Arbuckle, 1999), EQS (Bentler, 2004), and LISREL (Joreskog & Sorbom, 1996), although the procedures for multilevel latent models are somewhat difficult to implement at times because the programs were not specifically written for multilevel analyses. MPLUS (Muthen & Muthen, 2004) is a structural equation modeling program that has specifically incorporated features for estimating multilevel models and is well suited to specify and test a variety of different multilevel latent variable models including mixture of latent class and latent growth models. Undoubtedly, the features of the above programs are likely to change as technology and knowledge change.

Internet Resources

There are several useful Internet resources on multilevel and latent variable analysis. For multilevel analysis, it is useful to begin by going to comprehensive websites that give a variety of information on multilevel research including publications, newsletters, workshops, multilevel datasets, software reviews, and useful links to other websites. Examples include the UCLA Multilevel Modeling Portal (www.ats.ucla.edu/stat/mlm/) and the Web site of the Center for Multilevel Modeling (<http://multilevel.ioe.ac.uk/index.html>). The latter Web site provides a comprehensive list of references on multilevel modeling, an excellent set of reviews of computer software for performing multilevel analyses, and a library containing multilevel datasets that you can download for purposes of teaching and training in the application of multilevel models. There is also an active Internet discussion list where subscribers discuss conceptual and statistical problems in multilevel modeling ranging from elementary to advanced issues (www.jiscmail.ac.uk/lists/multilevel.html).

SEMNET is an excellent electronic mail network for anyone interested in discussing with researchers on any topics related to SEM and latent variable analyses. The website has an amazing archive of the discussions, organized by month dating back to 1993 (<http://bama.ua.edu/archives/semnet.html>).

The RMNET is a question-and-answer network for members of the Research Methods Division of the Academy of Management. The questions may be related to any research method issue concerning design, measurement and data analysis. Subscribers to RMNET include a diversity of researchers ranging from beginning graduate students to established scholars who have published on advances in analytical strategies. More information including how to join the RMNET are available on <http://division.aomonline.org/rm/rmnet.html>.

Several researchers also maintained their personal websites on specific analytical strategies. For example, David Kenny's website provides useful information on mediation analysis (<http://davidakenny.net/cm/mediate.htm>) and Herman Aguinis' website provides useful information on interaction analysis (<http://mypage.iu.edu/~haguinis/mmr/iindex.html>).

Internet resources are updated very rapidly and the reader should stay abreast by using search engines or contacting relevant professional organizations such as Division 5 (Evaluation, Measurement and Statistics) of the American Psychological Association and the Research Methods Division of the Academy of Management.

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